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Abstract

This paper presents an off-line writer-independent handwriting analysis system which utilizes both classical crisp and fuzzy methodologies to output possible personality traits of the writer. The design deploys an analytical handwriting analysis approach based on two primitives, the baseline and the slant angle of the characters. The objective of the design strategy is to present a group of parameters for handwriting analysis based on the text. These parameters allow for the classification of writing into different categories which could be used as a preliminary step for outputting the personality traits of the writer. Two parameters, the baseline and the slant-angle, are the inputs to a rule-base which outputs the personality trait category. The evaluation of the baseline is non-fuzzy (crisp) whereas the evaluation of the slant-angle utilizes the fuzzy paradigm.

The approach is based on a combination of classical geometric arithmetic evaluation and fuzzy control designs. For determination of the base line angle two methodologies are explored: the geometric-features based segmentation method and a method based on biologically inspired generation theories or the low pass filtering method. We utilize the geometric features evaluation for the baseline extraction since it proves more robust with respect to the variations of the handwriting in an off-line environment.

For determination of the slant type a fuzzy technique is adopted to determine the contributions of the slant-type angle to each of the five variations of the slant-type categories. The uncertainties in the system model are expressed by fuzzy-valued model parameters with their membership functions derived from experimental data. In total five variations of slant type are considered. These include extreme left, controlled left, vertical, controlled right and extreme right.

Fifteen personality traits PT1 – PT15 were identified and sets of rules formulation were created, (e.g., If Input1 is "level" and "Input2" is "Controlled Left" then Output is PTx.)

The proposed approach takes advantage of two differing methodologies that have clear outputs to evaluate two attributes of handwriting. The outputs are utilized to determine a personality trait. The system can be further enhanced by including more parameters such as size of letters, spacing between letters and other attributes of handwriting as part of the inputs for trait determination.

Key words, writer independent, hand writing analysis, fuzzy evaluation, personality traits,

1. INTRODUCTION

To the extent that hand writing is the outward expression of one's personality, hand writing analysis is an important tool for identifying personality traits. Handwriting has long been studied by numerous disciplines including experimental psychology, neuroscience, engineering, computer science, anthropology, education, forensic science, etc. from different aspects and for different purposes ([1], [2], [3], [4],[5], [6], [7]). From the computer science perspective, the types of analyses involved are the recognition, the interpretation and the verification of handwriting. Handwriting recognition is the task of transcribing a language message represented in a spatial form of graphical marks into a computer text, for example, a sequence of 8-bit ASCII characters.

Handwriting recognition can be classified into two types: off-line and online modes. Off-line handwriting recognition can be regarded as an extended field of OCR (Optical Character Recognition) and lacks the interactive nature of on-line handwriting recognition provided by the digital ink. Off-line data is two-dimensional in structure because of its image representation and has a typical size of a few hundred kilobytes per word. Since an image has no granted provision to distinguish its foreground and background, the first step of an off-line recognition, called "thresholding" ([8], [9], [10]), is to separate the foreground pixels from the background in the input. Unlike on-line handwriting, a written image also has a line thickness whose width depends on both the writing instrument used and the scanning process. Hence the next processing step is to apply a class of techniques called "thinning" or "skeletonization" ([11], [12]) which tries to shed out redundant foreground pixels from the input. These early preprocessing steps are necessary for off-line recognition but are, in general, expensive computationally and imperfect. They may also introduce undesirable artifacts in the result, for example, "spurs" in the thinning process ([11], [12]).

Another classifier in handwriting recognition is the class of writer-independent and writer-dependent systems. Writer-independence means that the system can handle the idiosyncrasies of multiple people's writing styles, and a writer-dependent system is trained and optimized to recognize a single person's writing. Due to the tremendous variety of writing styles writer-independent recognition systems are extremely complex and resource intensive. On the other hand, a writer-dependent system is trained with only one user and expectedly has less variability in the writing data, leading to smaller number of character subclasses and higher accuracy. Most likely, writer-dependence may not be very meaningful to off-line recognition systems because of the nature of many of their applications, for example, postal code sorting and recognizing the amounts of bank checks. In the case of on-line recognition, writer-dependence makes more sense since the system will typically serve as an input method to computers used personally by single user and is not intended to be shared by multiple users[16].

Handwriting analysis or graphology as it is commonly called is an important technique that can be utilized to discern a possible personality characteristic trait of the person. Among the many aspects of handwriting that can serve as scheme to predict personality traits are baseline, size of letters, connecting strokes, spacing between letters, words and lines, starting strokes, end-strokes, word-slant, speed of handwriting, width of margins, and others. Due to the proliferation of hand held computers and mobile technology handwriting recognition is one of the most challenging tasks and exciting areas of research in computer science. In spite of the growing interest in the field no satisfactory solution is available. Because of its inherent ambiguities and complexities graphology is most apt to be applied to a system design having a combination of crisp and fuzzy logic.

The large body of the work done in this area encompasses word recognition problems, which involve matching a digital image of handwriting word to a lexicon. Many handwriting recognition methods involve segmentation of an image into sub images before applying word-recognition problems. The input to the computer program will be a digital image of word and lexicon, which is a list of strings representing the possible identities of the word. The program segments the input word into primitives and applies the matching process that finds the closest match to an assembled set of primitives. The program then assigns the coincidence value to each segment that corresponds to a match. The coincidence values are combined to produce an overall match score. The program uses the score to rank the strings in the lexicon according to closely they match the image. The top-ranked string is the recognition result [17].

In this paper an offline writer independent handwriting analysis system is proposed. The handwriting text, when presented to our offline system, is converted into a two dimensional image format. The subsequent stage of feature extraction is comprised of two sub stages. The first sub stage is utilizing the crisp methodology and is the baseline extraction. This stage consists of the detection of a set of perceptual anchorage points (more precisely, the inflexion points) used to determine the direction of the baselines. In the second fuzzy-evaluation sub-stage a fuzzy control technique is used where the input is made up of the slant-angle of each character on the line. The combination of the base line type and the contribution of the slant-angle are used to out put a set of personality traits. Fuzzy control can be interpreted as an approximation technique for a control function based on typical, specified input-output tuples that are represented by fuzzy sets. The principal idea behind the fuzzy-control is to define a control function on the basis of the linguistic control rules that describe an adequate control strategy.

2. SYSTEM DESIGN

2.1 System design overview

The system design considered for handwriting analysis is an off-line handwriting recognition system. Figure 1 represents the block diagram of the proposed handwriting analysis system.

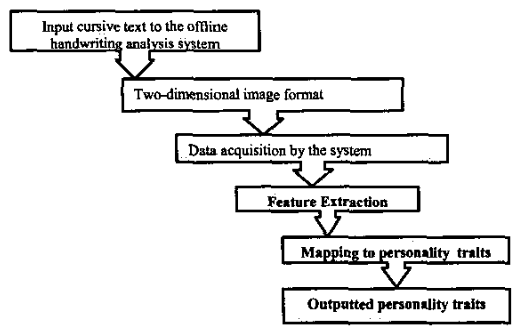

Figure 1. Block Diagram of the Handwriting Analysis

2.2 Features' Evaluation (Determination of Rule-Base Inputs)

2.2.1 Non-Fuzzy Stage for Baseline extraction

Four different "ledger" lines; the ascender line, the descender line, the baseline and the center line bound the characters in a line of text. The baseline is the most pronounced line which has been used for the system. The ascender line and the descender line are not well pronounced because ascenders and descenders occur too infrequently and their height has a large variance. Thus, we restrict our crisp methodology to that of the baseline.

This stage takes the baseline slope as the input. An Internal baseline is formed by joining the lowest middle case letters. Eight categories of baseline slopes are considered. These include level, ascending, descending, convex, concave, baseline falling and rising more than once, constant baselines and ascending words and lastly constant baselines, and descending words. Figure 2 depicts the categories of baselines. The baseline shape can thereafter be assigned to the standard curve shapes by tracing the curvature of the baseline. Next two methodologies are explained for determining the baselines.

2.2.2. *Methods for determining the baselines*

In order to determine the baselines for the handwriting text two methods are considered. The first method (M1) utilized in the design of our system is reported in [13] and is further explained in the next section. The second method (M2) involves performing a low pass filtering. The noise suppression technique used in this method is based on handwriting-generation theories [14]. It tries to eliminate perturbations in the velocity signal with the minimum modifications of the character geometry. For this purpose, a low pass filter is applied to the velocity signal, with a cut-off frequency of 10 Hz [15] and a window length of f/10 where f is the sampling frequency of the digitizing pad.

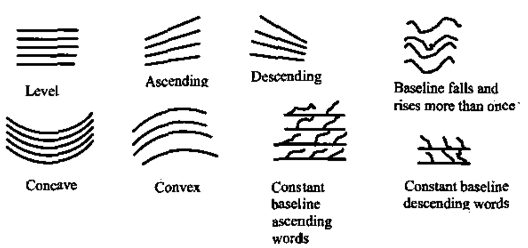

Figure 2. Categories of Baselines

The low pass filter attenuates high frequency components of a signal suppressing the noisy content of the signal, in this case associated handwritten text. Both methods are suitable for real time processing. However the second method (M2) is slower whereas the geometric method M1 is more robust with respect to the variations of the handwriting speed. Method M2 depends on the way the character is drawn, and therefore has the problems with calligraphic or extremely fast handwriting. Method M1 is described below

I. Line Detection

The set of connected chain-code elements forms foreground objects which are called continua. The baseline is found based on the local minima of all continua in y-direction. They are assumed to be locally straight even though lines of text curve over the complete width of the page. Local minima indicate, for the most part, points on the baseline and on the descender line with the majority stemming from baseline minima. Thus, the only line stretching over the whole width of the page and being made up of local minima from continua that are close enough together and locally straight, should be the baseline. Finding the baseline is carried out in four steps:

1. Potential baseline segments (pBLSs) are found that are segments of straight lines through local minima of the chaincode.
2. Baseline segments (BLSs) are selected or constructed from the pBLSs.
3. Baselines are created by joining BLSs which represent the same baseline. The parameter settings that are used for the processes described below are h_{sc} stands for the average height of small characters (distance between baseline and center line), w_c means the average width of a character.

II. Detection of Potential Baseline Segments (pBLSs) based on geometric features evaluation method (MI)

The pBLSs are created from local minima of all continua on the page. Local minimum vertices v^i_{min} are marked. A pBLS consists of a direction α and an ordered list of at least four vertices. Let $d^v_{x,max} = 3.4 \cdot w_c$ and $d^v_{y,max} = 0.2 \cdot h_{sc}$. Adjacent vertices in this list must not be further apart than dvx,max. None of the vertices may vary by more than dvy,max from the straight line connecting these vertices and defined by the direction α. pBLSs are created independently for each v^i_{min} and for each direction at increments of 1^0 within $\pm 20\ ^0$ (range found to be sufficient experimentally). New vertices v^j_{min} are added that lie in direction α constrained by the above-mentioned distance and deviation tolerances. The search for a pBLS terminates when no new vertices can be added.

III. Creating Baseline Segments (BLSs)

After finding all possible pBLSs, each vertex may belong to more than one pBLS. First, pBLS are excluded that devide by more than $\pm 7^0$ from the main direction of all pBLS. This direction is estimated from the histogram of directions of all pBLS. The remaining set of pBLSs still contains wrong segments. The next step creates a subset of baseline segments (BLSs) from the set of pBLSs. BLSs are selected according to the following rules: The number of

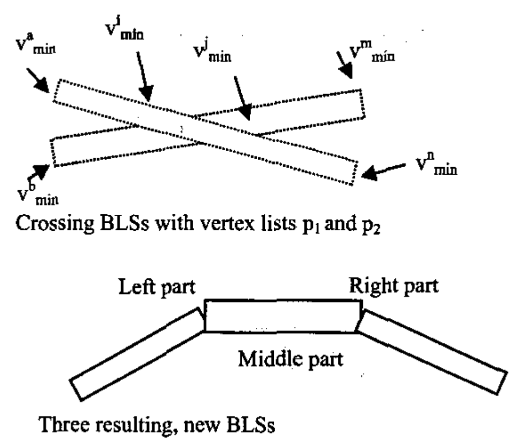

Figure 3. Potential Baseline

strokes above the BLS must be larger than that below it. The BLS must not be completely contained in another pBLS in an adjacent direction with a smaller vertical deviation of the included vertices. The BLS must not be intersected by a longer pBLS that includes it in horizontal direction. This is the case if the vertex lists p_1 and p_2 of two crossing pBLSs exist with $p_1 = \{v^a_{min}, \ldots, v^i_{min}, \ldots, v^j_{min}, \ldots, v^m_{min}\}$ and $p_2 = \{v^b_{min}, \ldots, v^i_{min}, \ldots, v^j_{min}, \ldots, v^n_{min}\}$ (shown in Fig. 3).Such line segments are separated into three subsets.The middle part is the set of vertices. vimin vjmin that is contained in p_1 as well as in p_2. One subset on the left side and one subset on the right side is chosen. In order to come to a decision between the subsets $v^a_{min}, \ldots, v^i_{min}$ and $v^b_{min}, \ldots, v^i_{min}$ and between the subsets $v^j_{min}, \ldots, v^m_{min}$ and $v^j_{min}, \ldots, v^n_{min}$, the one is chosen that contains the larger number of vertices.

IV. Creating Baselines

Elements of the set of BLSs are joined in order to form baselines. The process starts with the leftmost and uppermost BLS that is not part of a baseline and attempts to create a baseline by adding the next BLS. The process proceeds until no more BLS can be added. It is repeated for new baselines until no BLS exists that is not part of a baseline.

V. Determining direction of the baseline to assign it one of the nine categories of the lines

1. Draw a tangent to each of the segments at inflection points to determine the overall direction of the input line segment. We compute the local geometric features, namely the point curvatures and the point tangent angles. Firstly we compute the tangent angle at each point. This is approximated as the direction angle from the current point to the next point.
2. That is, for the two consecutive points) $p_i=(x_i,y_i)$ and $p_{i+1}=(x_{i+1},y_{i+1})$,the tangent angle θ_i of p_i is $\theta_i = \text{acos}(x_i - x_{i+1})/\text{dist}(p_i,p_{i+1})$ where dist(.) is the Euclidean distance between the two points. The curvature k_i at p_i is the then approximated as the amount of the direction angle change around point p_i That is, k_i is computed as the absolute amount of angle change from θ_{i-1} to θ_i multiplied by the sign that is plus if the angle change is clockwise, or minus if it is counter-clockwise. Following the direction of the different tangents at different segments the overall shape of the baseline can be determined. The end result of the methodology adopted is the assignment of the handwriting text line to one of the baseline slope categories.

2.2.3 Fuzzy Evaluation Stage

The input to this stage is the angle of the slant of the characters in the hand writing sample. In total five variations on the slant types are considered. These include extreme left, controlled left, vertical, controlled right and extreme right. The range is defined as follows: 0-60 is extreme left, 30-90 is controlled left,60-120 is vertical, 90-150 is controlled right and 120-180 is extreme right. Figure 4 depicts the membership distribution function. The slant of the handwriting text shall belong to each of the above five categories by varying membership degrees which shall be calculated based on the input range and the angle of the slant.

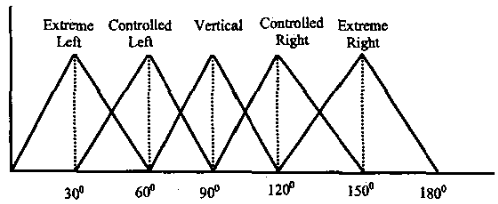

Figure 4. Membership Distribution Function

2.3 Rule Base Formulation

2.3.1 Output Personality Trait Categories

The fifteen categories of personality traits outlined in table 1 are the outputs of the fuzzy handwriting system.

PT1: Stable, Reliable, Unhappy, Self-conscious, Arrogant
PT2: Level headed, Realistic, Ambitious,Determined, Objective
PT3: Organized, Realistic, Cautious, Detached, Pessimistic
PT4: Stable, Reasonable, Altruistic, Friendly, Sociable, Warm
PT5: Reliable, Realistic, Affectionate, Involved, Jealous, Irritable
PT6: Ambitious, Energetic, Insecure, Cynical, Self absorbed
PT7: Involved, Optimistic, Abstracted, Independent, Objective, Shy
PT8: Joyful, Faith in the future, Independent, Reliable, Tenacious, Unsentimental
PT9: Energetic, Excited, Altruistic, Impulsive, Sentimental
PT10: Unrealistic, Busy, Expressive, Emotional, Unstable
PT11: Critical, Pessimist, Cynical, Insecure, Evades reality, Unhappy
PT12: Discouraged, Weak, Introverted, Cautious, Shy, Inhibited
PT13: Depressed, Unwell, Cautious, Cold, Detached, Impartial, Unsentimental
PT14: Fatalist, fatigued, adaptable, Impulsive, Sentimental
PT15: Critical, Tired, Jealous, Emotional, Irritable, Unstable, Quitter

Baseline type/Slant Angle	Extreme Left	Controlled Left	Vertical	Controlled Right	Extreme Right
Level	PT1	PT2	PT3	PT4	PT5
Ascending	PT6	PT7	PT8	PT9	PT10
Descending	PT11	PT12	PT13	PT14	PT15
Convex	PT12	PT6	PT8	PT4	PT10
Concave	PT3	PT2	PT5	PT6	PT12
Baseline falling and rising more than once	PT6	PT7	PT3	PT5	PT9
Constant Baseline and ascending words	PT10	PT7	PT13	PT4	PT7
Constant baselines and descending words	PT13	PT7	PT3	PT6	PT15

Table 1.List of Personality Traits

2.3.2 Calculation of membership degree for the personality trait category:

A fuzzy control approach is adopted in this context, since the input parameter baseline slope is associated with a crisp non-fuzzy evaluation stage hence there is no membership degree associated with this parameter; though this parameter can be used with the rule-base formulation; there is no metric contribution by the baseline to the fuzzy control methodology. In other words, we can say that though there is contribution by the baseline input parameter to the rule-base for determining the output personality trait evaluation, but there is no metric contribution by this parameter to the degree associated with this output trait category. Table 2 is used for determining the output personality traits and the degree contribution of each of them to the handwritten-cursive text.

Rule No.	Input1 (Baseline)	Degree Contribution	Input2 (Slant Type)	Degree	Output	Degree (minimum of degrees)
1	Level	1	Controlled Left	0.7	PT2	0.7
2	Ascending	1	Vertical	0.9	PT8	0.9
3	Concave	1	Controlled Left	0.4	PT2	0.4

Table 2.Determining the membership degree of the output personality traits

Rule Base formulation is a set of "if–then" rules:

If Input1 is "level" and "Input2" is "Controlled Left" then Output is PT2

If Input 1 is "Ascending" and Input2 is "Vertical" then Output is PT8.

For each rule the membership degree of the second of the antecedents (in this context is the slant type) is chosen as the membership degrees for the rule's consequent. This membership degree is considered as the weight for the rule's consequent. When there is more than one membership degree for a consequent, the maximum degree is chosen for that consequent. Hence, at that point a membership degree is assigned to each linguistic output value. For instance, Rule 1 and Rule 3 both provide the same output category (PT2). Eventually, the membership degree that shall be assigned to the trait category PT2 will be the maximum of the two degrees that is 0.7 shall be assigned to the category PT2.

In the scenario example given above; there are two rules being fired outputting different trait categories; the first is PT2 which has membership degree of 0.7 associated with it and PT8 which has a membership degree of 0.9 associated with it.

3. CONCLUSION

In this paper a scheme for handwriting analysis is proposed. A special merit of the work is the proposed design of an offline writer-independent handwriting analysis system utilizing a combined crisp and fuzzy approach to determine individual's personality traits. The shift from holistic word approaches to an analytical approach is the main paradigm of the paper. We make use of two primitives, namely the baseline and the slant angle for the inputs to the rule-base. The first part of the paper deals with the non-fuzzy methodology and is based on anchorage points (more specifically inflexion points of the tangents to the baseline) to determine the direction of the baseline. For the baseline extraction of our system two segmentation methods were considered. The use of the first method based on geometric features in our design instead of the biological models based low-pass filtering is justified because it is faster and more robust with respect to variations in handwriting speed. The second part is fuzzy evaluation stage and is concerned with the contribution of the slant angle to one of the five assigned directions. The inputs are fed to the rule base and a fuzzy control technique is used for the final determination of the personality traits. Finally, each personality type will be assigned a membership degree outputted from the rules reflecting the possibility that the individual has the particular personality traits.

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